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*Publication date:*  
2007

*Citation for published version (APA):*

Fu, X., & Shen, Q. (2007). *Knowledge representation for fuzzy model composition*. 47-54.  
<http://hdl.handle.net/2160/401>

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# Knowledge Representation for Fuzzy Model Composition

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**Abstract**—Compositional Modelling (CM) has been applied to synthesize automatically plausible scenarios in many problem domains with promising results. However, due to the lack of capability to deal with imprecise or ill-defined information, there is a pressing need to improve the robustness and accuracy of the existing CM work. This paper presents a more flexible knowledge representation formalism that combines fuzzy set theory and recently developed CM methods to support automating the process of generating plausible scenario spaces. The proposed knowledge representation incorporates both fuzzy parameters and fuzzy constraints into the representation of conventional model fragments. The fuzzy model composition process is illustrated by means of a simple worked example for aiding in crime investigation.

## I. INTRODUCTION

One of the hallmark contributions of qualitative reasoning is the method for creating models automatically for a specific task given a problem domain theory. Compositional Modelling (CM) [2] [6] (which has already become standard in qualitative reasoning) has been employed to synthesize and store plausible scenario spaces effectively and efficiently in many problem domains (e.g. physical [5], [9], [10], ecological [7], [11] and criminological [12]). The use of CM enables the construction of scenario descriptions automatically under widely varying circumstances without having to rely on an overly large knowledge base. This is rooted in the observation that in a scenario space the constituent parts of different scenarios are not normally unique to any one specific scenario, and that there are potentially many scenarios that possess common or similar properties locally or globally. The scenario elements and their relationships can therefore be modelled as generic and reusable fragments and they only need to be recorded once in the knowledge base.

Given a specific task, the plausible models which can solve or explain this task can be modelled in a variety of ways. Such model fragments are generally applicable to various scenario models, hence this results in a significantly increased efficiency and flexibility. For example, for applications like serious crime detection and prevention, rather than describing each scenario individually, a wide range of composing states and events, say factually and potentially available evidence, investigating actions and hypotheses can be captured in abstract form and be organized and stored in a knowledge base. Given obtained evidence (e.g. crime location and involved victims), scenario descriptions that may explain such evidence can then be synthesized dynamically by combining those potentially relevant composing states and

events which are instantiated with the evidence and facts provided.

Having recognized this, CM has been applied to the building of an intelligent crime investigation decision support system [12] to assist human investigators by automatically constructing plausible scenarios and analyzing the likely further investigating actions with promising results. Despite the promising performance and results of the existing system, it is assumed that the model fragments and expert knowledge within the knowledge base can all be expressed by precise and crisp information. However, in reality, the degree of precision of the available evidence and intelligent data can vary greatly. In many cases, precise information is relatively more difficult to obtain than low resolution information. For instance, in cognitive modelling, different people may hold different conceptual models of the world. Indeed, under many circumstances, it is difficult to express a view with a crisp value. For example, consider the police discovered the dead body of Smith in his bedroom. Bob who is the next-door neighbour witnessed somebody going into Smith's house; however, it is difficult for Bob to state an accurate height for that person (e.g. 180 cm). Intuitively, he might just describe the height of the person as tall, short or average.

Furthermore, in the existing work, each scenario fragment employs a set of probability distributions to represent the likelihood of its associated outcomes, and these are described in numerical forms. However, such assessment of likelihood typically reflects the expertise and knowledge of experienced investigators and is normally available in linguistic terms instead [3]. The use of seemingly accurate numeric probabilities suffers from an inadequate degree of precision. It would be more appropriate and desirable to incorporate a measurement of imprecision in depicting the probability distributions.

Fuzzy set theory offers a useful means of capturing and reasoning with uncertain information at varying degree of precision. Although fuzzy set theory has been applied to addressing various problems, it has not been integrated to compose a fuzzy model. This paper presents an initial attempt to extend the existing CM work to allow for representing and use of vague knowledge and linguistic probability [1], [4]. It follows the existing literature in applying CM to support crime investigation by generating automatically plausible crime scenarios. This problem domain is well suited to illustrating the underlying ideas of integrating fuzzy set theory in CM, since the scenario fragments as well as the

causal relations between them are highly subjective and often related to inexact and vague information.

The development of fuzzy CM mechanisms involves two conceptually distinct aspects: 1) fuzzification of parameters in the model fragments, including the identification and definition of fuzzy variables in a generic sense; and 2) fuzzy probabilistic assessment of the constraints between the states and events of the world in question.

After presenting a brief overview of the basic concepts of CM, the knowledge presentation of both fuzzy parameters and fuzzy constraints in defining fuzzified scenario fragments is given. This is followed by an illustration of applying fuzzy model fragments to a small crime investigation problem, showing the composition process of a plausible scenario space from given evidence and facts. The final section concludes this paper and points out future work.

## II. BASIC CONCEPTS OF COMPOSITIONAL MODELLING

In CM, the knowledge base of the model-building system consists of a number of generic scenario fragments, interchangeably termed model fragments as above, which represent generic relationships between domain objects and their states for certain types of partial scenario. In particular, a scenario fragment has two parts that encode domain knowledge: 1) the relations between domain elements which are often represented in a form that is similar to conventional production rules but in a much more general format where predicates are used to describe the properties of these domain elements; and 2) a set of probability distributions that represent how likely it is that the corresponding relationships are related.

More formally, a scenario fragment  $\mu$  is a tuple  $\langle v^s, v^t, \phi^s, \phi^t, A \rangle$  and is represented in the following form:

```

If { $\phi^s$ }
Assuming { $A$ }
Then { $\phi^t$ }
Distribution  $\phi^t$ 
 $\{v_1^s \dots v_n^s \rightarrow v_1^t : q_1 \dots v_m^t : q_m\}$ 

```

where

- $v^s$  is a set of variables named source-participants, referring to already identified objects of interest in the partial scenario, which can be real, artificial or conceptual objects.
- $v^t$  is a set of variables named target-participants, representing new objects that will be added to the partial scenario description if the model fragment is instantiated (i.e. when both the conditions and assumptions are presumed to be true).
- $\phi^s$  is a set of relations called structural conditions, whose free variables are elements of  $v^s$ . Normally, the structural conditions appear in the antecedent part and describe how the source-participants are related to one another, often encoded in the form of predicates.
- $\phi^t$  is a set of relations called post-conditions, whose free variables are elements of  $v^s \cup v^t$ . Normally, the

post-conditions appear in the consequent part and define new relations between source-participants and/or target-participants, also often encoded in the form of predicates.

- $A$  is a set of assumptions, referring to those pieces of information which are unknown or cannot be inferred from other scenario fragments, but they may be presumed to be true for the sake of performing hypothetical reasoning.

The **If** statement describes the required conditions for a partial scenario to become applicable. These conditions must be factually true or logical consequences of other instantiated fragments.

The **Assuming** statement indicates the reasoning environment. With the purpose of performing hypothetical reasoning, this environment specifies the uncertain events and states which are presumed in a partial scenario description.

The **Then** statement describes the consequent when the conditions and presumed assumptions hold. They may represent a piece of new knowledge or relations which are derived from the hypothetical reasoning.

The **Distribution** statement indicates the probability distributions of the consequent variables or those of their relations. The left hand side of the “implication” sign in each instance of such a statement is a combination of variable-value pairs, involving antecedent and assumption variables, and the right hand side indicates the likelihood of each alternative outcome if the fragment is instantiated.

For example, the following scenario fragment shows a piece of generic forensic knowledge that, assuming that suspect  $S$  overpowers victim  $V$ , there is a 75% chance that fibres will be transferred from  $S$  to  $V$ :

```

If {suspect( $S$ ), victim( $V$ )}
Assuming {overpowers( $S, V$ )}
Then {transfer(fibers,  $S, V$ )}
Distribution transfer(fibers,  $S, V$ ) {
    true, true, true  $\rightarrow$ 
    true: 75%, false: 25% }

```

Given a collection of such local model fragments and some observations (evidence), CM applies an inference procedure to create a space of scenario descriptions at a global level. As the details of this procedure are very similar to what is to be employed in fuzzy CM to be reported later, they are omitted here. Interested readers can refer to [12] for further details.

## III. FOUNDATIONS OF FUZZY CM

This section focuses on the creation of a structured knowledge representation scheme which is capable of storing and managing vague or ill-defined data including facts, evidence and assumed information. Effort has been made to encode fuzzy scenario fragments in a pre-specified format. The research developed here is loosely based on knowledge representation given in [12] and its related work; however, it is adapted to represent imprecise and uncertain information, including both parameters and constraints.

### A. Fuzzy parameters

For many problems, there may be many variables that share similar properties while most of these properties only involve minor variations from one another if encoded computationally, in terms of knowledge representation. This is independent of whether the variables are fuzzy or not. For example, variables such as quantity, volume and proportion all reflect the concept of capacity. This group of variables may all be expressed by linguistic terms such as large, average or small (which can be conveniently represented by fuzzy sets). Therefore, when defining a fuzzy variable, rather than redefining a new quantity space for it completely from scratch each time, it has a natural appeal to group fuzzy variables which share something in common into the same class. In each class, the common features shared by the variables are extracted and represented by an abstract variable with its quantity space specified over a normalized universe of discourse. The quantity space of a variable belonging to a given class is created by inheriting the common features from the abstract variable and by embellishing it with new or modified properties.

To enable this development, fuzzy taxonomies that describe vague states and events for use in the scenario fragments are introduced here. A taxonomy is considered to be a hierarchy, where those variables at a lower level are more specific than their ancestors and represent a more specialized group of fuzzy variables. In so doing, fuzzy variables in a CM knowledge base are organized in a structured manner. This does not only improve the efficiency of storing knowledge via reusing abstract fuzzy variables, but also helps reveal both the commonality and speciality of different variables. More importantly, the use of fuzzy taxonomies supports the construction of scenario spaces in a systematic and concise manner due to the inheritance property of the hierarchies.

Consider, for instance, the taxonomies shown in Fig. 1. The first organises a set of fuzzy variables relating to an abstract fuzzy variable named *Measurement*. Hence, fuzzy variables height, distance, width, depth and length share certain properties in defining their quantity spaces as they inherit such common features from the abstract *Measurement* variable; all of them can be measured with respect to a certain measurable unit and can be described as long, average or short. Similarly, the variables in the second taxonomy are all used to describe levels of different concepts. Although they may denote rather distinct or even seemingly irrelevant properties (e.g. temperature and difficulty), they all take on values from the same underlying abstract quantity space in terms of various levels such as high, average or low.

Note that, in these taxonomies, even the fuzzy variables which are classified into different classes may still have some more generic and deep underlying commonalities. For instance, temperature in the second taxonomy is also a measurable variable. Hence, from a more generic aspect, they may still be allocated to a superclass which is more abstract. However, in order to maintain the clarity of representation and the comprehensibility of inference drawn

from such representations, fuzzy taxonomies are not built in the most generic way possible, but are classified with easy interpretability in mind.

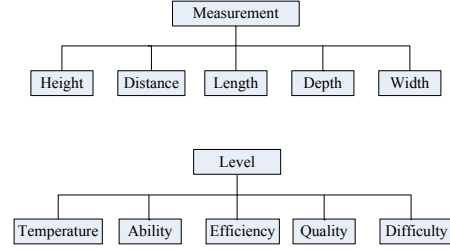


Fig. 1. Example taxonomies of fuzzy variables

From above, it is clear that in defining scenario fragments fuzzy variables can be divided into two types: abstract or non-abstract. Abstract fuzzy variables are actually variable classes that cannot be instantiated themselves in an effort to describe any actual scenario and non-abstract fuzzy variables are those that can be instantiated. Clearly, in Fig. 1 *Measurement* and *Level* are abstract fuzzy variables, and depth, distance, height, efficiency, etc. are non-abstract variables.

In implementation, abstract fuzzy variables are indicated by means of the keyword **abstract**. Defining such a variable involves specifying the following fields:

- **Name:** A constant that uniquely identifies the abstract fuzzy variable.
- **Universe of discourse:** The domain of the abstract variable. The default definition is  $[0, 1]$ . Any descendant of an abstract fuzzy variable can modify the universe of discourse according to their physical dimension.
- **Cardinality of partition:** The number of fuzzy sets which jointly partition the universe of discourse. This is represented by a symbol  $n$  which will be substituted by a positive integer in a lower level non-abstract variable.
- **Quantity Space:** A set of ordinal relationships that describe the value of a continuous parameter. Here, these relationships are represented by the membership functions of each fuzzy set that jointly cover the partitioned domain.

For example, the aforementioned abstract fuzzy variable *Level* can be defined as follows (adhering to the conventional representation style of model fragments):

Define **abstract** fuzzyvariable {  
**Name:** Level  
**Universe of discourse:**  $[0, 1]$   
**Cardinality of partition:**  $n$   
**Quantity space:**  

$$f_{s_1} = \left[0, 0, \frac{1}{n-1}\right]$$

$$\dots$$

$$f_{s_i} = \left[\frac{i-2}{n-1}, \frac{i-1}{n-1}, \frac{i}{n-1}\right]$$

$$\dots$$

$$f_{s_n} = \left[\frac{n-2}{n-1}, 1, 1\right]$$
 }

It would be inefficient and practically unnecessary to store and manipulate fuzzy sets with arbitrarily complex membership functions. Only the triangular membership functions are considered in this initial work. Thus, a quantity space specification consists of an ordered list of triples comprising the start, top and end points of each membership function. For both computational and presentational simplicity, triangular membership functions in which the edge of a fuzzy set's membership function is exactly intersected to the centroid of the neighboring one are used in this paper. For example, assume  $n = 5$ , then the defined quantity space of the abstract fuzzy variable *Level* is shown in Fig. 2.

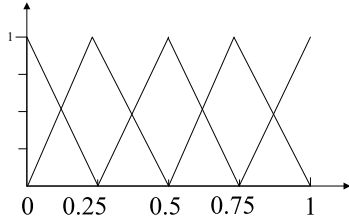


Fig. 2. A quantity space

Non-abstract fuzzy variables are identified by means of the absence of the keyword **abstract**. Such definition involves "is-a" relationships in which a non-abstract fuzzy variable is said to inherit from an abstract fuzzy variable. It requires addition of fields that are specific to the variable under definition, with shared commonalities already defined in the corresponding superior abstract fuzzy variable. In fuzzy CM, such new fields are defined as follows:

- **Is-a:** The name of an abstract fuzzy variable which refers to the immediate parent of the current fuzzy variable in a given taxonomy.
- **Scalar:** A constant which is used to scale up or down the normalized universe of discourse of the corresponding abstract variable.
- **Unit:** The variable's physical dimension. If a fuzzy variable has no unit, a default value of none is set for this field.
- **Name of fuzzy sets:** The name of each fuzzy set in the defined quantity space.
- **Unifiability:** The declaration of a unifiable property of the variable, specified by a predicate.

The following example defines a non-abstract fuzzy variable named *Chance* that inherits from *Level*.

```

Define fuzzyvariable {
  Name: Chance
  Is-a: Level
  Cardinality of partition: 5
  Scalar: 1
  Unit: none
  Name of fuzzy sets: {extremely_unlikely,
    slim_chance, likely, very_likely, good_chance}
  Unifiability: Chance(X)
}

```

Obviously, this non-abstract fuzzy variable *Chance* is a kind of *Level*. Due to property inheritance, its universe of discourse equals to the normalized universe of discourse multiplied by the scalar over the corresponding physical dimension. Its quantity space is evenly partitioned by 5 fuzzy sets which are described respectively by the five linguistic terms given. Also due to inheritance, the membership functions of those fuzzy sets are obtained once again by multiplying the corresponding key points in each fuzzy set by the scalar.

### B. Fuzzy constraints

In CM, knowledge is normally expressed as constraints or relations which must be obeyed by certain variables involved in a given problem domain. For example, velocity and duration relations often appear in physical reasoning systems; population growth and competition relations often appear in ecological reasoning system; length and angle relations often appear in spatial reasoning systems. Such constraints as used in the existing work require numerical values to quantify the probability of a consequence's occurrence, as previously illustrated.

Since such subjective probability assessments are often the product of barely articulate intuitions, the seemingly numerically precise expressions may cause loss of efficiency, accuracy and transparency [1], [3], [4]. Under many circumstances, an expert may be unwilling or simply unable to suggest a numerical probability. For example, consider the following scenario: a dead body of Smith was discovered at home and the cause of the death was suspected to be suicide. A psychologist was then invited to examine the mental condition of Smith by analysing his diary. Consultation with the psychologist is unlikely to yield much beyond vague statements like "According to his diary, he is extremely unlikely to kill himself" or "According to his diary, he stood a good chance of killing himself". Therefore, the initial work developed here models the vagueness of the probability distribution in terms of subjective linguistic probabilities. Rather than using numerical representation as in the literature, a fuzzy variable called *Chance* which inherits the properties of the abstract fuzzy variable *Level* is introduced to capture subjective probabilistic assessments. Both the *Chance* variable and its superior abstract variable *Level* have been presented in previous section.

Similar to the existing approach, a scenario fragment includes a set of probability distributions over the possible assignments of the consequent  $\phi^t$ , for those interested combinations of assignments to the variables within the structural conditions and assumptions. Note that, it is not required to define each combination, the probability distribution only focuses on those of interest. This can be generally represented by:

$$P(a_1 : v_1, \dots, a_m : v_m \rightarrow c : v_{cp}) = f s_p \quad (1)$$

where  $a_i : v_i, i \in \{1, 2, \dots, m\}$  denotes the assignment obtained by assigning  $v_i$  to variable  $a_i$ ,  $c : v_c$  has a similar

interpretation, and  $fs_p$  is a member of the quantity space that specifies the fuzzy variable *Chance*.

As an example, the following fragment illustrates the concepts and applicability of fuzzy constraints:

```

If {height(S), height(V)}
Assuming {attempted_to_kill(S, V)}
Then {difficult_level(overpower(S, V))}
Distribution difficult_level(overpower(S, V)) {
    tall, short, true →
    easy: good_chance, difficult: slim_chance }

```

It describes a causal relation holding among structural condition  $a_1$  and  $a_2$ , assumption  $a_3$  and post-condition  $c$ , here

$a_1 = \text{height}(S)$  indicates the height of a suspect  $S$ , which is a fuzzy variable that takes on values from a predefined quantity space of {very\_short, short, average, tall, very\_tall}.  $a_2 = \text{height}(V)$  indicates the height of a victim  $V$ , whose possible value assignment is the same as  $S$ .

$a_3 = \text{attempted\_to\_kill}(S, V)$  describes that suspect  $S$  attempted to kill victim  $V$ , representing a conventional boolean predicate.

$c = \text{difficulty\_level}(\text{overpower}(S, V))$  describes the difficulty level for suspect  $S$  to overpower victim  $V$ , with possible assignments being easy, average and difficult.

Note that, when defining probability distributions in scenario fragments, the names of those variables within the structural conditions, assumptions and post-conditions (e.g.  $a_1, a_2, a_3$  and  $c$ ) are omitted when such omissions do not affect the interpretation of the meaning of the associated values, for the sake of presentational simplicity. Thus, the probability distributions can be rewritten as follows:

$$v_1, v_2, \dots, v_m \rightarrow v_{c1} : fs_1, \dots, v_{cp} : fs_p$$

The above fragment reveals a general relation between the heights of two people involved in a fight and the difficulty level for one to overpower the other, and it can be applied to modelling various scenarios. For example, this fragment covers a fuzzy production rule which indicates that if suspect  $S$  is tall, while victim  $V$  is short, and the suspect indeed attempted to kill the victim, then the suspect stands a good chance of overpowering the victim easily. Conversely, if the suspect is shorter than the victim and he indeed attempted to kill the victim, then there is only a slim chance for the suspect to overpower the victim easily.

#### IV. APPLICATION TO CRIME INVESTIGATION: OUTLINE OF SCENARIO COMPOSITION

The proposed knowledge representation formalism and how it is used to support CM is illustrated here with a sample application to the generation of plausible scenarios reflecting a crime situation in which a number of fibers matching Bob's clothes (Bob is the suspect) have been found on the dead body of Dave. Relevant evidence and the key scenario fragments of the sample knowledge base are presented in Appendix A. From the given facts, collected evidence and

this knowledge base, a structural scenario space can be generated by joint use of two conventional inference techniques named *abduction* and *deduction*. Note that since the degree of precision of the information (including both predefined knowledge and available evidence/facts) can vary greatly, the collected evidence and the knowledge base cannot in general be matched precisely. Thus, a fuzzy matching method is applied for scenario fragment instantiation.

##### A. Initialization

To generate a space of plausible scenarios, collected evidence and any available facts are firstly entered. The present example shows one piece of evidence in which a number of fibers collected from Dave's body have been identified matching the fibers of Bob's clothes, and two available facts in which Dave is known to be the victim and Bob is under suspicion. The result of this initialization phase is shown in Fig. 3.

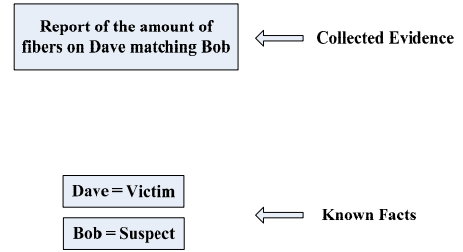


Fig. 3. Result of initialization

##### B. Backward chaining phase

This phase involves the abduction of all domain objects and their states that might cause the available evidence. These plausible causes are created by instantiating the conditions and assumptions of the scenario fragments in the knowledge base, whose consequences match the collected evidence in the emerging scenario space. After that, the newly created instances of all plausible causes are recursively used in the same manner as the original piece of evidence, instantiating all relevant fragments and adding new nodes that correspond to the instantiated conditions and assumptions to the emerging scenario space. For the present example, this phase leads to what is shown in Fig. 4.

A brief explanation of how such *abduction* phase works with respect to the following sample fragment and collected evidence/facts is given below:

```

If {degree_of_fight(S, V)}
Assuming {transfer(X, S, V), find_match(X, V, S)}
Then { evidence(amount(transferred(X, V, S))) }
Distribution evidence(amount(transferred(X, V, S)))
{intensive, true, true → many: good_chance, few: slim_chance
 weak, true, true → many: slim_chance, few: good_chance}

```

Given the collected evidence that a number of fibers matching Bob's clothes have been found on the dead body of Dave, which matches the consequent variable of the above scenario fragment, the variables within the structural conditions and assumptions  $X, S$  and  $V$  are firstly instantiated with



fibers, Bob and Dave, respectively. The resulting instantiated nodes (e.g. Transfer fibers from Bob to Dave, Degree of fight between Bob and Dave and Find fibers on Dave matching Bob) are then added to the emerging scenario space.

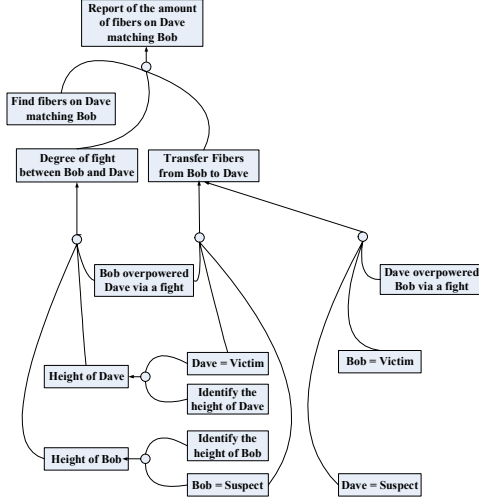


Fig. 4. Result of backward chaining

1) *Fuzzy matching*: To allow instantiation of a fuzzy scenario fragment when given a piece of evidence, the extended compositional modeller requires matching specific data items with broader and relatively subjective information in the knowledge base. As aforementioned, the evidence and the knowledge base cannot always be matched precisely. Under many circumstances, however, the values of the involved fuzzy variables do not have to be identical, partial matching suffices. Such matching is done by the following process.

First, find those scenario fragments that involve the same variables as the underlying fuzzy variables that describe the collected evidence. For example, in the backward chaining phase, the consequence and collected evidence in the above example both contain the amount of the transferred substance  $X$  (with the amount being a fuzzy variable). Second, identify the degree of the match between the evidence and the found scenario fragments. Third, return a matched scenario fragment for instantiation if the match degree is larger than a predefined threshold, otherwise, no match between them is found.

Fig. 5 illustrates how such a fuzzy match mechanism actually works. Given the collected evidence that a number of transferred fibers exist, a match degree of 0.8 is obtained by calculating the maximum membership value over the overlapping area between “a number of” and “many” fuzzy sets. Note that more complex calculi for matching degree may be developed; however, for computational simplicity and thanks to the employment of triangular fuzzy sets only, this straightforward matching method is adopted here. Clearly, much remains to be done in order to have a more general approach regarding the set-up of the important threshold used in the third step. Yet, this does not affect the understanding of the underlying inference techniques introduced herein.

#### C. Forward chaining phase

While all plausible causes of the collected evidence and some pieces of additional evidence may be introduced to the

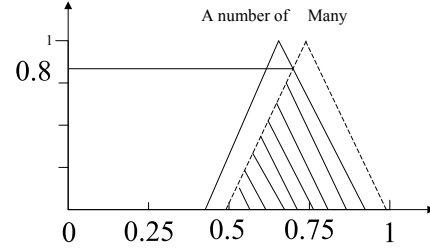


Fig. 5. The fuzzy matching mechanism

emerging scenario space during the backward chaining phase, the forward chaining phase is responsible for extending the scenario space by adding all plausible consequences of the fragments whose conditions and assumptions match the instances created in the last phase. This produces potential pieces of evidence that have not yet been identified but may be used to improve the plausible scenario description.

This procedure applies logical *deduction* to all the scenario fragments in the knowledge base, whose conditions and assumptions match the existing nodes in the emerging scenario space. The actual matching method used is basically the same as that used previously (except step 1 obviously). For the running example, based on those newly introduced nodes such as “Bob = victim”, “Dave = suspect” and “Dave overpowered Bob via a fight”, their deduced corresponding consequences are then created and added to the emerging scenario space. Fig. 6 depicts the resulting scenario space that may be the outcome of this phase (depending on the actual knowledge base used).

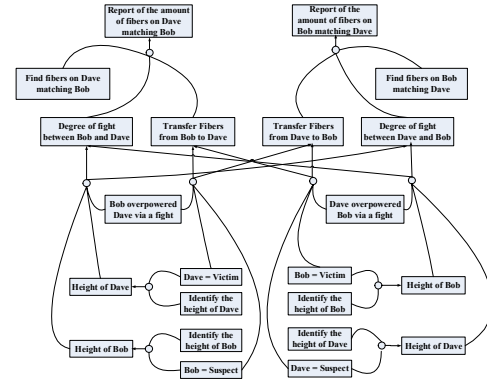


Fig. 6. Result of forward chaining

#### D. Removal of spurious nodes

In the backward chaining phase, some spurious nodes may have been added to the emerging scenario space. Such nodes are root nodes in the space graph which are neither facts or instantiated assumptions nor the justifying nodes that support the instantiated assumptions. This step aims to remove the spurious nodes and their immediate consequences. In this example, the emerging scenario space containing the following information that Dave is both the suspect and victim at the same time, and the same for Bob. Since Dave is known to be the victim whereas Bob is known as the suspect, the nodes “Dave = suspect” and “Bob = Victim” as well as their directly supported nodes can be removed from this emerging

scenario space. The remaining scenario space is shown in Fig. 7.

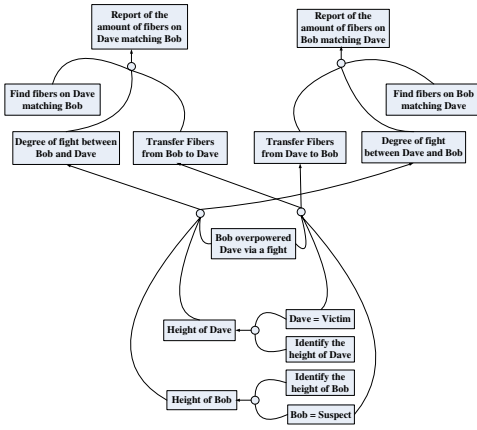


Fig. 7. Result of spurious node removal

#### E. Use of generated scenario space

Once the plausible scenario space is generated, it provides effective assistance for crime investigators by allowing them to seek potential answers to a range of possible queries. For instance, an investigator may query the system for scenarios by inputting his/her interested evidence or hypotheses. Also, the investigator might discover that a tall person was observed entering the crime scene on a CCTV camera, and wonders whether this would rule out homicidal death. The system can answer this type of question by adding this new evidence to the set of collected pieces of evidence and modifying the generated scenario description to establish whether the new evidence indeed supports the hypothesis. Note that compared with previous work, the present approach provides more flexible query support, as it has the capability to deal with fuzzy queries.

### V. CONCLUSIONS

This paper has enriched and adapted the knowledge representation formalism in existing CM work, to enable it to represent, store and support reasoning about vague and imprecise data, by the use of fuzzy sets. The new knowledge representation formalism concerns both fuzzy parameters and fuzzy constraints by incorporating them into the representation of conventional model fragments. The applicability of the proposed method is illustrated by means of a simple worked example for aiding inexperienced crime investigators in speculating about all plausible causes of the collected evidence.

Note that, attempts to model probabilistic terms using fuzzy sets have proven more successful. For example, a relatively sophisticated experimental method for eliciting fuzzy models of probabilistic terms has been developed in [13] and the inter-subjective stability of generated terms has been examined with promising results. In addition, it has been reported in [14] that verbal expressions of probabilistic uncertainty can be “more accurate” than numerical values in estimating the frequency of multiple attributes by experimental studies. Whilst there are outstanding problems

such as context sensitivity with the fuzzy approach to modelling probabilistic terms, these psychometric studies are unanimous in preferring fuzzy descriptions of probability to numerical estimates.

While the proposed method presented here shows powerful potential functionalities and significant benefits in supporting qualitative reasoning, there are still many open problems and areas that require further research. In particular, the proposed method is not yet able to analyze the generated scenarios space and therefore to provide evidence collection strategies for decision support. In order to improve the effectiveness of evidence collection, the generated plausible scenarios need to be evaluated by means of calculating the most likely scenario.

Also, the fuzzy constraints within a single scenario fragment are defined by employing a fuzzy variable named *Chance*. However, when dynamically composing these potential relevant scenario fragments into plausible scenario descriptions, the fuzzy constraints will be propagated from individual fragments to their related ones. How to combine and propagate fuzzy probabilities, in conjunction with the backward and forward propagation of the fuzzy matching degrees, in an emerging model space is a tough problem that needs to be taken into account in further research. Original work as represented in [3], [4] may serve as a starting point for this.

While solving complex problems, the size of the knowledge base and the number of attributes involved might become very large, the abduction and deduction inference mechanism is quite expensive to generate the scenario spaces and is only practical for simple knowledge bases. In order to enhance the effectiveness and efficiency of the generation of scenario spaces by selecting the most relevant attributes, another important piece of future work concerns the use of dynamic constraint satisfaction problem (DCSP) [8] techniques where activity constraints are employed to dynamically determine which attributes should be activated in the problem, thus the problem of dimensionality may be greatly reduced.

### ACKNOWLEDGMENTS

This work was supported in part by UK EPSRC grant EP/D057086. The first author was also supported by a UK ORS award. The authors are grateful to Mark Lee, Jeroen Gunning and Ruiqing Zhao for their helpful discussions, but will take full responsibility for the views expressed in this paper.

### APPENDICES

#### Key Sample Data and Scenario Fragments

```
Define action{
  name = find_match
  description = find the substance X on V matching S
  unifiability = find_match(X,V,S)}
```

```
Define action{
  name = identify_height
  description = identify the height of P
  unifiability = identify(height(P))}
```

```
Define evidence{
  name = report_of_amount
  description = report of the amount of X
  unifiability = evidence(amount(X))}
```



```

Define fuzzyvariable {
name = height
is-a = measurement
cardinality of partition = 5
scalar = 250
unit = centimeter
names of fuzzy sets = {very.short, short, average, tall,
very.tall}
unifiability = height(P)}

Define fuzzyvariable {
name = amount
is-a = capacity
cardinality of partition = 5
scalar = 1
unit = none
names of fuzzy sets = {none, few, several, a.number.of, many }
unifiability = amount(X)}

If {suspect(S),victim(V)}
Assuming {overpower(S,V)}
Then { transfer(X,S,V)}
Distribution transfer(X,S,V){
true,true,true→true:good.chance, false:slim.chance}

If {suspect(S),victim(V)}
Assuming {overpower(S,V)}
Then { transfer(X,V,S)}
Distribution transfer(X,V,S){
true,true,true→true:good.chance, false:slim.chance}

If {person(P)}
Assuming {Identify(height(P))}
Then { height(P)}
Distribution height(P){
true,true→true:1, false:0}

If {degree.of.fight(S,V)}
Assuming {transfer(X,S,V),find.match(X,V,S)}
Then { evidence(amount(transferred(X,V,S)))}
Distribution evidence(amount(transferred(X,V,S)))
{intensive,true,true→many:good.chance,few:slim.chance
weak,true,true→many:slim.chance,few:good.chance}

If {height(V), height(S)}
Assuming {overpower(S,V)}
Then {degree.of.fight(S,V)}
Distribution degree.of.fight(S,V)
{tall,short,true→intensive:slim.chance,weak:good.chance
short,tall,true→intensive:slim.chance,weak:good.chance
tall,tall,true→intensive:good.chance,weak:slim.chance
short,short,true→intensive:good.chance,weak:slim.chance}

If {height(V), height(S)}
Assuming {overpower(S,V)}
Then {degree.of.fight(V,S)}
Distribution degree.of.fight(V,S)
{tall,short,true→intensive:slim.chance,weak:good.chance
short,tall,true→intensive:slim.chance,weak:good.chance
tall,tall,true→intensive:good.chance,weak:slim.chance
short,short,true→intensive:good.chance,weak:slim.chance}

Translation {unifiability = overpower(S,V)
description: S overpowers V}

Translation {unifiability = degree.of.fight(S,V)
description: the degree of fight between S and V}

Translation {unifiability = transfer(X,S,V)
description: X were transferred from S to V}

Translation {unifiability = find.match(X,V,S)
description: find the substance X on V matching S}

Translation {unifiability = amount(X)
description: the amount of X}

Translation {unifiability = identify(height(P))
description: identify the height of person P}

Translation {unifiability = evidence(amount(transferred(X,V,S)))
description: report of the amount of transferred X found on V
matching S}

```

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